Novel Wavelet ANN Technique to Classify Interturn Fault in Three Phase Induction Motor

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Abstract

Early detection of faults in stator winding of induction motor is crucial for reliable and economical operation of induction motor in industries. Whereas major winding faults can be easily identified from supply currents, minor faults involving less than 5 % of turns are not readily discernible. The present contribution reports experimental results for monitoring of minor short circuit faults in stator winding of induction motor. Motor line current has been analyzed using modern signal processing and data reduction tool combing Park's Transformation and Discrete Wavelet Transform (DWT). Feed Forward Artificial Neural (FFANN) based data classification tool is used for fault characterization based on DWT features extracted from Park's Current Vector Pattern. An online algorithm is tested successfully on three phase induction motor and experimental results are presented to demonstrate the effectiveness of the proposed method.

Keywords: Induction motor, ANN, Fault detection, DWT, Park's vector pattern.

1. Introduction

Electric motors are the critical components of many industrial processes and are frequently integrated in commercially available equipment and industrial processes. Squirrel cage induction motors have a dominant over the other motors due to their low cost, ruggedness, low maintenance and operation with easily available power supply. Motor faces various stresses during operating conditions and these stresses may lead to several failures. Stator inter turn fault is the most common type of fault in electric motor. If these faults are undetected, it may lead to machine failure. Hence condition monitoring becomes necessary for induction motor to detect any fault in early stage in order to avoid disastrous failures.

Several schemes for detecting inter turn faults are proposed. Some of the reported techniques necessitates mathematical model of the system.[1]-[2]. In [1] modeling and simulation of with inter turn fault for diagnoses have been reported. . The models have been successfully used to study the transient and steady state behavior of induction motor with short circuited turns. Number of techniques uses frequency spectrum of line currents to detect inter turn faults [3]-[4]. Fourier transform is not appropriate to analyze a signal that has transient characteristics such as drift, abrupt changes and frequency trends. An induction motor fault diagnosis using stator current envelopes for broken rotor bars and inter turn short circuit in stator winding have been proposed in [5]. According to Stavrou et.al. fault detection scheme is based on measuring negative sequence impedance. [6]. Monitoring the high order spectra of radial

machine vibration for detection of inter turn fault is proposed in [7]. A wavelet packet for extracting useful information from vibration signals has been employed in [8]. Inter turn fault detection based on measuring the neutral voltage is proposed in [9], but it is limited to star connected machines with an accessible neutral. The detection of fault using dqo components of stator currents with wavelet transform is ideal [10]. This scheme however involves computation burden.

Wavelet techniques for fault monitoring and diagnosis of induction motor are increasing because these techniques allow performing stator current signal analysis during transients. Wavelet transform can be used for a localized analysis in time-frequency or time- scale domain. It is thus a powerful tool for condition monitoring and fault diagnosis. In [11] inter turn fault is detected with the help of absolute peak d1 coefficients of stator currents, which are then fed to ANN. But this scheme requires a detail mathematical modeling.

In this paper ANN based approach is been proposed and found to be an effective alternative for detecting inter turn fault in induction motor. Artificial Immune system has abilities of learning memory and self adaptive control. In addition ANN can perform continuous nonlinear functions online through the use of inexpensive monitoring devices. These devices obtain necessary measurements in noninvasive manner. Main problems facing the use of ANN are the selection of best inputs and choice of ANN parameters so as to make the structure compact to create highly accurate networks. Many input features require a significant computational effort and thus can result in low success rate.

The present work documents experimental results of stator inter turn minor fault monitoring in induction motor. Line current signals recorded from motor terminals are processed through a suitable data reduction stage involving Park's Transformation followed by DWT to obtain judicious features corresponding to different fault conditions. Spectral energies contained in detail d1-d5 level of Park's current vector (Id and Iq) are selected as inputs to ANN. Results so obtained demonstrate suitability of the proposed technique for stator turn to turn fault monitoring achieving 100 % of classification accuracy.

2. **Signal Processing by Park's Transformation.**

The three phase line currents fed to induction motor can be suitably represented by two dimensional (2 D) system by the use of current Concordia vector [11]-[12] obtained by Park's Transformation. As a function of mains phase variables (ia,ib,ic) the motor current park's vector component id, iq are

$$i_d = \sqrt{2/3}\ i_a - 1/\sqrt{6} i_b - 1/\sqrt{6} i_c \tag{1}$$

$$i_q = 1/\sqrt{2} i_b - 1/\sqrt{2} i_c \tag{2}$$

Under ideal conditions, three-phase currents lead to a Park's vector with the following components

$$i_d = \sqrt{6}/2 I \sin wt \tag{3}$$

$$i_q = \sqrt{6}/2I(\sin wt - \pi/2) \tag{4}$$

where- I- maximum value of the supply phase current

w_s- Supply frequency;

t -time variable

The corresponding representation of id-iq is a circular locus cantered at origin of the coordinates under balanced condition. Under abnormal conditions equations 3 and 4 are no longer valid and as a result the observed pattern differs from reference pattern. The philosophy of Park's vector approach is thus based on identifying unique signature pattern, obtained corresponding to the motor current Park's vector representation.

3. Wavelet Transform

Wavelet analysis is about analyzing the signal with short duration finite energy functions which transform the considered signal into another useful form. This transformation is called Wavelet Transform (WT). Let us consider a signal f(t), which can be expressed as-

$$f(t) = \sum_l a_l \, \varphi_l(t) \tag{5}$$

Where, l is an integer index for the finite or infinite sum. Symbol a_l are the real valued expansion coefficients, while $\varphi_l(t)$ are the expansion set.

If the expansion (5) is unique, the set is called a basis for the class of functions that can be so expressed. The bases are orthogonal if-

$$\langle \varphi_l(t), \varphi_k(t) \rangle = \int \varphi_l(t) \varphi_k(t) dt = 0 \quad k \neq l \tag{6}$$

Then coefficients can be calculated by the inner product as-

$$\langle f(t), \varphi_k(t) \rangle = \int f(t) \, \varphi_k(t) \, dt \tag{7}$$

If the basis set is not orthogonal, then a dual basis set $\varphi_k(t)$ exists such that using (7) with the dual basis gives the desired coefficients. For wavelet expansion, equation (5) becomes-

$$f(t) = \sum_k \sum_j a_{j,k} \, \varphi_{j,k}(t) \tag{8}$$

In (8) j and k are both integer indices and $\varphi_{jk}(t)$ are the wavelet expansion function that usually form an orthogonal basis. The set of expansion coefficients a_{jk} are called Discrete Wavelet Transform (DWT).

There are varieties of wavelet expansion functions (or also called as a Mother Wavelet) available for useful analysis of signals. Choice of particular wavelet depends upon the type of applications. If the wavelet matches the shape of signal well at specific scale and location, then

large transform value is obtained, vice versa happens if they do not correlate. This ability to modify the frequency resolution can make it possible to detect signal features which may be useful in characterizing the source of transient or state of post disturbance system. In particular, capability of wavelets to spotlight on short time intervals for high frequency components improves the analysis of signals with localized impulses and oscillations particularly in the presence of fundamental and low order harmonics of transient signals. Hence, Wavelet is a powerful time frequency method to analyze a signal within different frequency ranges by means of dilating and translating of a single function called Mother wavelet.

The DWT is implemented using a multiresolution signal decomposition algorithm to decompose a given signal into scales with different time and frequency resolution. In this sense, a recorder-digitized function a0(n), which is a sampled signal of f(t), is decomposed into its smoothed version a1(n) (containing low-frequency components), and detailed version d1(n) (containing higher-frequency components), using filters h(n) and g(n), respectively. This is first-scale decomposition. The next higher scale decomposition is now based on signal a1(n) and so on, as demonstrated in Fig.1.
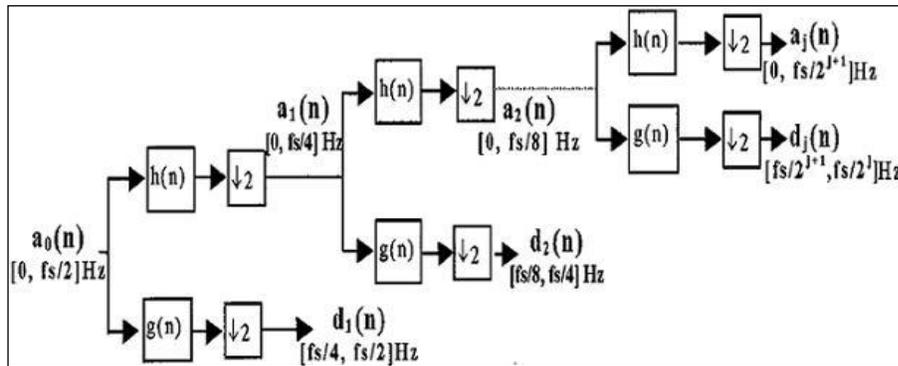

Fig 1: Multiresolution signal decomposition

The analysis filter bank divides the spectrum into octave bands. The cut-off frequency for a given level j is found by –

$$fc = fs \, / \, 2^{\,j+1} \tag{9}$$

where fs is the sampling frequency. The sampling frequency in this paper is taken to be 10 kHz and Table I shows the frequency levels of the wavelet function coefficients.

Table 1: Frequency levels of Wavelet Functions Coefficients

Decomposition Level	Frequency Components HZ
d1	5000-2500
d2	2500-1250
d3	1250-625
d4	625-312.5
d5	312.5-156.25
a5	0-156.25

4. Artificial Neural Network

ANNs are highly interconnected processing units inspired in the human brain and its actual learning process. Interconnections between units have weights that multiply the values which go through them. Also, units normally have a fixed input called bias. Each of these units forms a weighted sum of its inputs, to which the bias is added. This sum is then passed through a transfer function.

Prediction with NNs involves two steps: training and learning. Training of FFNNs is normally performed in a supervised manner. The success of training is greatly affected by proper selection of inputs. In the learning process, a neural network constructs an input–output mapping, adjusting the weights and biases at each iteration based on the minimization or optimization of some error measure between the output produced and the desired output. This process is repeated until an acceptable criterion for convergence is reached. The most common learning algorithm is the back propagation (BP) algorithm, in which the input is passed layer through layer until the final output is calculated, and it is compared to the real output to find the error. The error is then propagated back to the input adjusting the weights and biases in each layer. The standard BP learning algorithm is a steepest descent algorithm that minimizes the sum of square errors. In order to accelerate the learning process, two parameters of the BP algorithm can be adjusted: the learning rate and the momentum. The learning rate is the proportion of error gradient by which the weights should be adjusted. Larger values can give a faster convergence to the minimum. The momentum determines the proportion of the change of past weights that should be used in the calculation of the new weights.

In this paper, the fully-connected multilayer FFNNs is used and trained for discrimination of healthy and faulty condition with a supervised BP learning algorithm. The FFNN consists of an input layer representing the input data to the network, hidden layers and an output layer representing the response of the network. Each layer consists of a certain number of neurons; each neuron is connected to other neurons of the previous layer through adaptable synaptic weights *w* and biases *b,* as shown in Fig.2 (a) and 2 (b).

If the inputs of neuron j are the variables $x_1, x_2, . . , x_i, . . . , x_N$, the output u_j of neuron *j* is obtained as

$$u_j = \varphi \left(\sum_{i=1}^{N} w_{ij} x_i + b_j \right) \tag{10}$$

where w_{ij} is the weight of the connection between neuron *j* and *i*-th input; b_j is the bias of neuron *j* and φ is the transfer (activation) function of neuron *j*.

An FFNN of three layers (one hidden layer) is considered with N, M and Q neurons for the input, hidden and output layers, respectively. The input patterns of the ANN represented by a vector of variables $x = x_1, x_2, . . . , x_i, . . . , x_N$) submitted to the NN by the input layer are transferred to the hidden layer. Using the weight of the connection between the input and the

hidden layer and the bias of the hidden layer, the output vector $u = (u_1, u_2, \ldots, u_j, \ldots, u_M)$ of the hidden layer is determined.

The output u_j of neuron j is obtained as

$$u_j = \varphi\, hid\, (\sum_{i=1}^{N} w_{ij}^{hid}\; x_i + b_j^{hid}) \tag{11}$$

where w_{ij}^{hid} is the weight of connection between neuron *j* in the hidden layer and the *i*-th neuron of the input layer, b_j^{hid} represents the bias of neuron *j* and $\varphi\,hid$ is the activation function of the hidden layer.

The values of the vector *u* of the hidden layer are transferred to the output layer. Using the weight of the connection between the hidden and output layers and the bias of the output layer, the output vector $y = (y_1, y_2, \ldots, y_k, \ldots, y_Q)$ of the output layer is determined.

The output y_k of neuron *k* (of the output layer) is obtained as

$$y_k = \varphi\, out\, (\sum_{j=1}^{M} w_{jk}^{out}\; u_j + b_k^{out}) \tag{12}$$

where w_{jk}^{out} is the weight of the connection between neuron *k* in the output layer and the *j*-th neuron of the hidden layer, b_k^{out} is the bias of neuron *k* and $\boldsymbol{\varphi out}$ is the activation function of the output layer.

The output y_k is compared with the desired output (target value) y_k^d. The error E in the output layer between y_k and y_k^d $(y_k^d - y_k)$ is minimized using the mean square error at the output layer (which is composed of *Q* output neurons), defined by

$$E = \frac{1}{2} \sum_{k=1}^{Q} (y_k^d - y_k)^2 \tag{13}$$

Training is the process of adjusting connection weights *w* and biases *b*. In the first step, the network outputs and the difference between the actual (obtained) output and the desired (target) output (i.e., the error) is calculated for the initialized weights and biases (arbitrary values). In the second stage, the initialized weights in all links and biases in all neurons are adjusted to minimize the error by propagating the error backwards (the BP algorithm). The network outputs and the error are calculated again with the adapted weights and biases, and this training process is repeated at each epoch until a satisfied output y_k is obtained corresponding with minimum error. This is by adjusting the weights and biases of the BP algorithm to minimize the total mean square error and is computed as

$$\Delta w = w^{new} - w^{old} = -\eta\, \frac{\partial E}{\partial w} \tag{14a}$$

$$\Delta b = b^{new} - b^{old} = -\eta\, \frac{\partial E}{\partial b} \tag{14b}$$

where η is the learning rate. Equation (15) reflects the generic rule used by the BP algorithm. Equations (16) and (17) illustrate this generic rule of adjusting the weights and biases. For the output layer, we have,

$$\Delta w_{jk}^{new} = \alpha \, \Delta w_{jk}^{old} + \eta \, \delta_k \, y_k \qquad (15a)$$

$$\Delta b_k^{new} = \alpha \, \Delta b_k^{old} + \eta \, \delta_k \qquad (15b)$$

where α is the momentum factor (a constant between 0 and 1) and $\delta_k = y_k^d - y_k$

For the hidden layer, we get,

$$\Delta w_{ij}^{new} = \alpha \, \Delta w_{ij}^{old} + \eta \, \delta_j \, y_j \qquad (16a)$$

$$\Delta b_j^{new} = \alpha \, \Delta b_j^{old} + \eta \, \delta_j \qquad (16b)$$

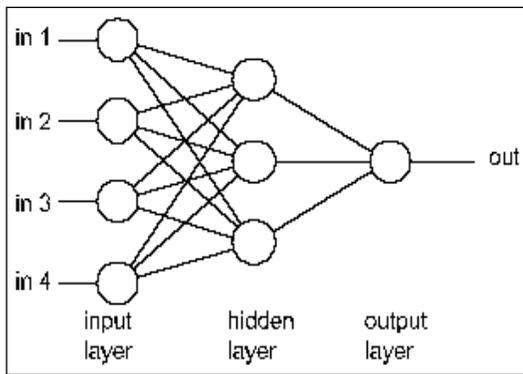where $\delta_j = \sum_k^Q \delta_k \, w_{jk}$ and $\delta_k = y_k^d - y_k$
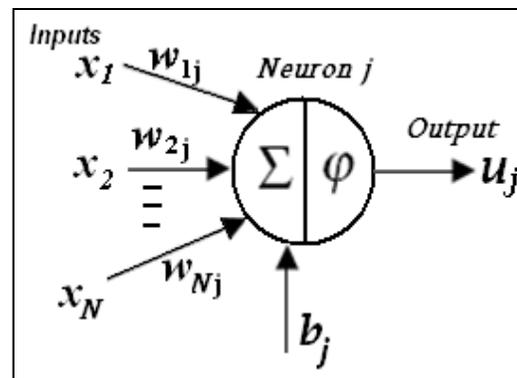

Fig. 2(a): Processing in ANN   Fig 2.(b): Architecture of ANN

5. Experimentation and Data Collection

For experimentation and data generation 2 H.P, 3 phase, 4 pole, 415 volts ,50 Hz squirrel cage induction motor made by the Leading Indian Electrical industry is used has been used for the analysis of inter-turn faults . Experimental setup of the same is shown in Fig 3.The motor used for experiment has 24 coils, 36 slots in all. Each phase comprising of eight coils, carries 300 turns. Therefore one of the three phases has been tapped where each tapping is made after every 10 turns near to the star point (neutral)..The tapings are drawn from the coils where each group comprises of approximately 70 to 80 turns. The spring and belt arrangement is used for the mechanical loading of the motor. With shown loading arrangement the motor was loaded to 75% of the full load and the rated full load. The current and voltage is then captured for no load, 75% of rated load and the rated full load of the motor.

In order to acquire the data, the Tektronix DSO, TPS 2014 B, with 100 MHz bandwidth and adjustable sampling rate of 1GHz is used to capture the current and voltage signal. The Tektronix current probes of rating 100 mV/A, input range of 0 to 70 Amps AC RMS, 100A peak and frequency range DC to 100KHz are used to acquire the stator current signals and the voltage probes of Tektronix make are used for acquiring the stator voltage signals. Approximately, 500 sets of signals are captured on different load conditions and at different mains supply conditions.

Stator current and phase voltage of the motor for different number of short circuited turns is then captured in order to compare with healthy condition of motor. Different experiments were conducted with 10 turns, 20 turns and 30 turns short circuited to access the performance of; and effect on the motor. Three currents I_a, I_b and I_c and voltage V_a were captured with sampling frequency of 10 kHz .This data is then processed and analyzed using MATLAB.

Fig.3: Experimental Set Up

6. Fault Feature Extraction Using DWT

Three phase line currents fed to induction motor are represented in two dimensional systems by Park's Transformation. For characterizing the faults suitable features need to be extracted from Park's vector pattern .An important step is the selection of mother wavelet to carry out the analysis. Several wavelet families with different mathematical properties have been developed. These wavelets are Gaussian,Mexican,Hat, Morlet,Meyer, Daubechies,Coiflet, Biorthogonal etc. For extraction of fault components after multiple test , it is seen that wide variety of wavelet families can give satisfactory results . In the proposed algorithm Daubechies-4 (DB-4) is used as the mother wavelet .

When DWT is applied to extract the scaling and wavelet coefficients from a transient signal, a large amount of information in terms of these coefficients is obtained. Although the information is useful, it is difficult for ANN to train /validate that large information. Another alternative is to input the energy contents in the detailed coefficients according to Parseval's Theorem.

$$\int f(t)^2 dt = \sum_k Cj(k)^2 + \sum_{x=1;j} \sum_k dx(k)^2 \qquad (17)$$

Where $f(t)$ Signal to be decomposed using DWT, Cj Approximation of the DWT at level j. dx Detail number x of the DWT.

The general meaning of Parseval's theorem is that the energy contained in any signal is equal to the summation of the energy contained in the approximation and details at any DWT decomposition level (j).As only the transients are being focused so only the second part of above equation (17) is Considered. In the proposed strategy Park's current pattern (Id and Iq) derived from induction motor line currents for healthy and faulty conditions are decomposed up to the fifth level using DB4 .
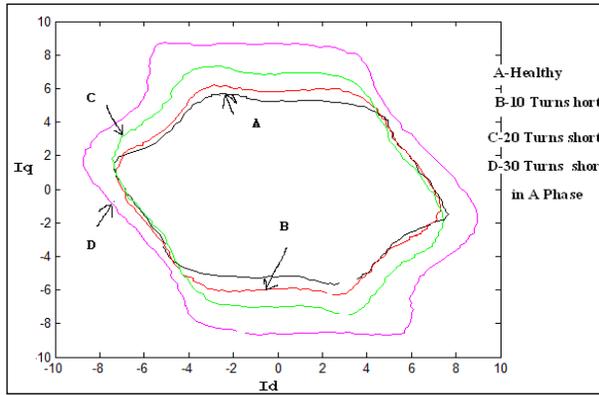
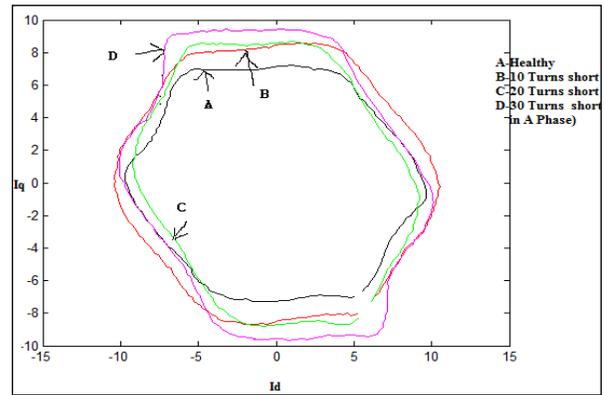Fig 4**:** Park's Pattern (For 75 % of Full Load)   Fig 4(b): Park's Pattern (For Full Load Condition)

Fig 4a and 4b shows Park's vector pattern obtained under healthy and fault conditions, involving different number of turns shorted in phase A for 75 % of full load and full load conditions respectively. Fig 5(a &b) & Fig 6(a &b) shows the decomposition of Park's current vector for healthy and faulty (20 Turns short circuited) conditions respectively. Energies of the level d1-d5 are calculated and are used as inputs to neural network.
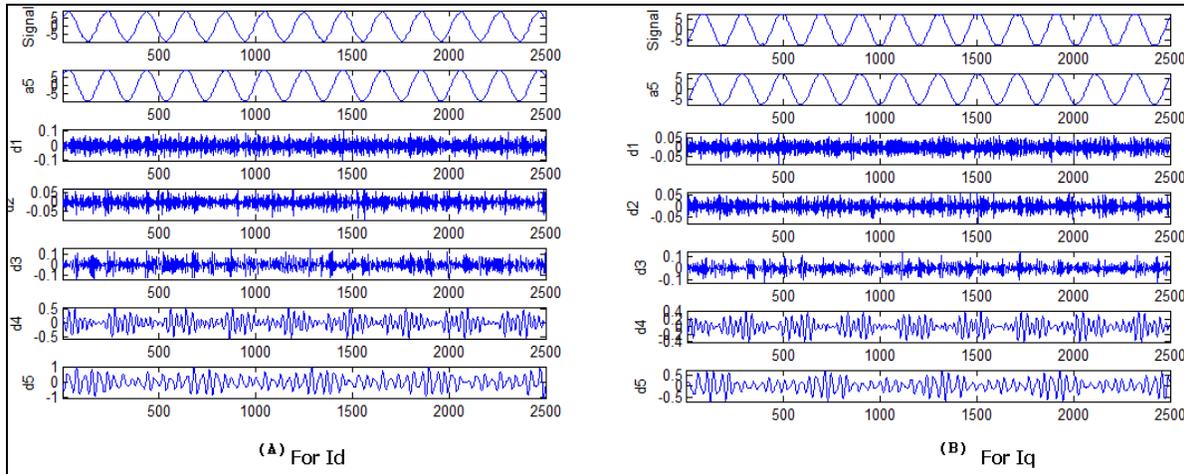

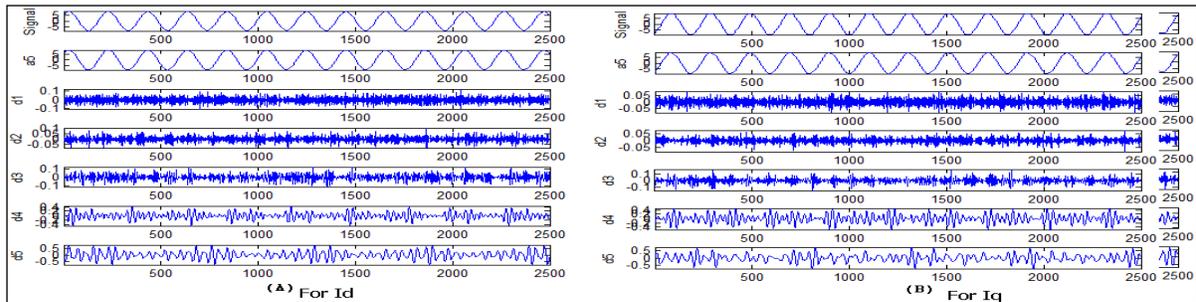Fig 5:.Wavelet Decomposition of Park's Current Pattern for Healthy Condition

Fig 6 :.Wavelet Decomposition of Park's Current Vector For 20 Turns short

7. Algorithm For Proposed Strategy

FANN is capable of discriminating healthy and faulty conditions of induction motor. Long term memory weights can be used at the processor level to take the decision regarding classification of healthy and faulty condition of motor. Steps for online detection scheme are-

1. Capture the three phase currents IA, IB and IC of induction motor using data acquisition system.
2. Apply Park's Transformation to obtain Park's current vector pattern (Id and Iq).
3. Calculate DWT of Id and Iq
4. Obtain the energies of decomposed levels d1-d5 using
5. $E = \sum_{i=1}^{n} x^2(i)$
   where x(i) is the discrete sequence representing a subset of detail coefficient sequence of d1 to d5.

The energy of decomposed levels d1-d5 is given to ANN as input data to discriminate the healthy and faulty condition.

8. Results And Discussion

An ANN with its excellent pattern recognition capabilities can be effectively employed for the fault classification of three phase induction motor. In this paper 3 layer fully connected FFANN neural network is used and trained with supervised   learning algorithm called back propagation. FFANN consists of one input layer, one hidden layer, and one output layer. Input layer consists of ten neurons, the inputs to these neurons are spectral energies contained in detail d1-d5 level of Park's current vector (Id and Iq). Output layer consists of four neurons representing healthy, ten turns short circuited, twenty turns short circuited, thirty turns short circuited of stator winding respectively. With respect to hidden layer it is customary that number of neurons in hidden layer is done by trial and error. Same approach is used in proposed algorithm.

Conjugate gradient back propagation and Levenberg Marquardt back propagation are used for training the network and average minimum of average minimum square error MSE on training and testing data is obtained. For both the training methods it is assumed that learning rate L.R.=0.8, Momentum=0.7,transfer function is TanhAxon ,data used for training purpose TR=50 % ,for cross validation C.V =20 %, for testing TS=30 %. With these assumptions variation of average MSE and percentage accuracy of classification for ten turns ,twenty turns and thirty turns short circuited in A phase of stator winding with respect to number of processing elements in hidden layer is obtained.

Table 2 shows variation of average MSE with respect to number of processing elements in hidden layers for the training method of Conjugate Gradient back propagation with Fletcher Reeves update ('traincgf'). Percentage accuracy of classification with respect to number of processing elements is hidden layer for the same is plotted in Fig 7.From fig is observed that for Conjugate Gradient training method seven numbers of processing elements in hidden layer are

required to get minimum MSE of 6.66 e^{-8} and it gives 100% classification for healthy and faulty conditions.

Table 2: MSE and Percentage Accuracy of classification for   Conjugate Gradient Method

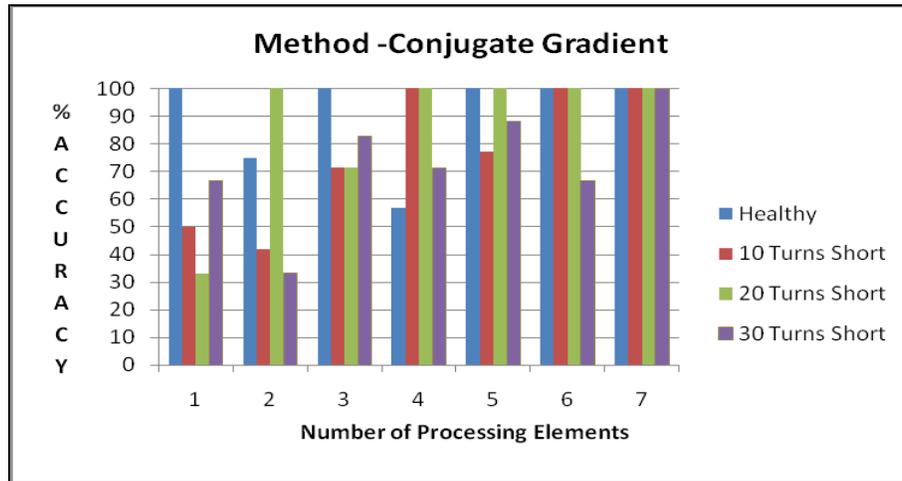| Number of P.E'S	MSE	Percentage accuracy of Classification			
		Healthy	10Turns short	20 Turns short	30 Turns short
1	0.413	100	50	33	66.7
2	0.194	75	42	100	33.33
3	0.00078	100	71.4	71.4	82.8
4	1.43 e^{-2}	57	100	100	71.4
5	3.13 e^{-2}	100	77	100	88
6	1.8 e^{-4}	100	100	100	66.66
7	6.66 e-8	100	100	100	100

Figure 7: Variation of   % Accuracy with number of   processing elements in hidden   layer.

9. Conclusion

This paper addresses the issue of stator inter turn short circuit fault monitoring in induction motor. Experimental results with less than five percent of turns short circuited in stator winding are presented. Line current signals recorded under fault conditions have been passed through series of signal processing and data reduction procedures involving Park's Transformation. Subsequently DWT is utilized to extract the features of faulty condition as against the healthy state of motor. Feed Forward Artificial Neural Network with Levenberg Marquardt as the training method and with four processing elements in hidden layer is then applied to classify the faults based on features obtained by DWT. Proposed methodology is useful in identifying inter turn fault even though only if three percent of turns of stator winding are short circuited and these further can be used as a preventive monitoring tool for minor inter turn fault in stator winding with 100 percent accuracy.

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